face-emotion-recongition

December 23, 2023

```
[400]: import tensorflow as tf
       import numpy as np
       import matplotlib.pyplot as plt
       import cv2
       import shutil
       import os
       from keras.preprocessing.image import ImageDataGenerator
       from keras.models import Sequential
       from keras import regularizers
       from keras.layers import Dense, MaxPooling2D, Flatten, Conv2D, Dropout
        →BatchNormalization, Activation
       from keras.callbacks import EarlyStopping, ReduceLROnPlateau
       from keras.optimizers import Adam, SGD
       from keras.utils import to categorical
       from sklearn.utils.class_weight import compute_class_weight
       from imblearn.over_sampling import SMOTE
[401]: | # # Define the path to your original dataset and the paths where you want to | |
       ⇔store your train and test datasets
       # original dataset dir = 'CK+'
       # train_dir = 'CK+train'
       # validate_dir = 'CK+validate'
       # test_dir = 'CK+test'
       # # Create directories for training and testing datasets if they do not exist
       # os.makedirs(train_dir, exist_ok=True)
       # os.makedirs(validate_dir, exist_ok=True)
       # os.makedirs(test_dir, exist_ok=True)
       # # Define the split ratio
       # train ratio = 0.7
       # # Loop through each emotion category in the original dataset
       # for emotion in os.listdir(original_dataset_dir):
             emotion_dir = os.path.join(original_dataset_dir, emotion)
```

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images = [f for f in os.listdir(emotion_dir) if os.path.isfile(os.
        ⇒path.join(emotion_dir, f))]
                 # Randomly shuffle the list of image filenames
       #
                 np.random.shuffle(images)
                 # Split the list of image filenames into training and testing sets
                 train_size = int(len(images) * train_ratio)
       #
                 validate_size = int(len(images)-len(images)*(15/100))
                 train_images = images[:train_size]
                 validate_images = images[train_size:validate_size]
                 test_images = images[validate_size:]
                 \# Create directories for the emotion category in the train and test
        \rightarrow datasets
                 train_emotion_dir = os.path.join(train_dir, emotion)
                 validate_emotion_dir = os.path.join(validate_dir, emotion)
                 test_emotion_dir = os.path.join(test_dir, emotion)
                 os.makedirs(train_emotion_dir, exist_ok=True)
                 os.makedirs(validate_emotion_dir, exist_ok=True)
       #
                 os.makedirs(test_emotion_dir, exist_ok=True)
                 # Copy the images into the corresponding directories
       #
                 for image in train_images:
                     shutil.copy(os.path.join(emotion dir, image), os.path.
        ⇒join(train_emotion_dir, image))
                 for image in validate images:
                     shutil.copy(os.path.join(emotion_dir, image), os.path.
        ⇒ join(validate_emotion_dir, image))
                 for image in test_images:
                     shutil.copy(os.path.join(emotion dir, image), os.path.
        ⇒ join(test_emotion_dir, image))
       # print("Dataset splitting complete")
[402]: # Create a data generator with augmentation
       trainDataGenerator = ImageDataGenerator(
           rescale=1./255, # Rescale the pixel values (normalization)
           width_shift_range=0.1, # Random horizontal shifts (15% of total width)
           height_shift_range=0.1, # Random vertical shifts (15% of total height)
           horizontal_flip=True, # Randomly flip inputs horizontally
           fill_mode='nearest',
           zoom_range=0.1,
           shear_range=0.1,
```

Get a list of all the image filenames in the emotion category

if os.path.isdir(emotion_dir):

#

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# Load images from the directory and apply the defined transformations
       trainingData = trainDataGenerator.flow_from_directory(
           'CK+train', # Path to the training data
           target_size=(48, 48), # Resize images to 48x48
           class_mode='categorical', # Labels will be returned in categorical format
           batch size=8
       )
       class labels = list(trainingData.class indices.keys())
       class_counts = np.zeros(len(class_labels))
       class_weights = compute_class_weight(class_weight = 'balanced', classes = np.
        →unique(trainingData.labels), y = trainingData.labels)
       class_weight_dict = {class_idx: weight for class_idx, weight in_
        ⇔enumerate(class_weights)}
       #smote = SMOTE(sampling_strategy='auto', random_state=42)
       #trainingData[0][0], trainingData[0][1] = smote.
        \rightarrow fit_resample(trainingData[0][0], np.argmax(trainingData[0][1], axis=1))
       print(class_weight_dict)
      Found 682 images belonging to 7 classes.
      {0: 1.0364741641337385, 1: 2.6332046332046333, 2: 0.7921022067363531, 3:
      1.8736263736263736, 4: 0.6765873015873016, 5: 1.6798029556650247, 6:
      0.5599343185550082}
[403]: | # Initialize an ImageDataGenerator for test data with rescaling
       validationDataGenerator = ImageDataGenerator(rescale=1./255, # Rescale the | 1
        ⇔pixel values (normalization)
       # Creates a data generator for the test dataset
       # flow from directory method loads images from a directory
       validationData = validationDataGenerator.flow_from_directory(
           'CK+validate', # Directory path for test images
           target_size = (48, 48), # Resizes images to 48x48 pixels
           class_mode = 'categorical', # Images are classified categorically
           batch_size=8
       )
       # validationData is now a generator that yields batches of test images and \square
        →their labels
       validationData.class_indices
```

```
Found 147 images belonging to 7 classes.
[403]: {'anger': 0,
        'contempt': 1,
        'disgust': 2,
        'fear': 3,
        'happy': 4,
        'sadness': 5,
        'surprise': 6}
[404]: testDataGenerator = ImageDataGenerator(rescale=1./255)
       testingData = testDataGenerator.flow_from_directory(
           'CK+test', # Directory path for test images
           target_size = (48, 48), # Resizes images to 48x48 pixels
           class_mode = 'categorical', # Images are classified categorically
           batch_size=8,
           shuffle = False,
       )
       testDataGenerator2 = ImageDataGenerator(rescale=1./255)
       testingData2 = testDataGenerator2.flow_from_directory(
           'data/test', # Directory path for test images
           target_size = (48, 48), # Resizes images to 48x48 pixels
           class mode = 'categorical', # Images are classified categorically
           batch_size=8,
           shuffle = False,
       testingData.class_indices
      Found 152 images belonging to 7 classes.
      Found 3589 images belonging to 7 classes.
[404]: {'anger': 0,
        'contempt': 1,
        'disgust': 2,
        'fear': 3,
        'happy': 4,
        'sadness': 5,
        'surprise': 6}
[405]: model = Sequential()
       model.
        Gadd(Conv2D(32,(3,3),padding="same",input_shape=(48,48,3),activation='relu'))
```

```
model.add(Conv2D(32,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(64,(3,3),activation='relu'))
model.add(Conv2D(64,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Conv2D(128,(3,3),activation='relu'))
model.add(Conv2D(128,(3,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Flatten())
model.add(Dense(128))
model.add(Dense(64))
model.add(Dense(32))
model.add(Dropout(0.25))
model.add(Dense(7,activation='softmax'))
opts = SGD(
    learning_rate=0.01, nesterov=True
model.

¬compile(optimizer=opts,loss='categorical_crossentropy',metrics=['accuracy'])
model.summary()
```

Model: "sequential_37"

Layer (type)	Output Shape	Param #
conv2d_184 (Conv2D)	(None, 48, 48, 32)	896
conv2d_185 (Conv2D)	(None, 46, 46, 32)	9248
<pre>max_pooling2d_100 (MaxPool ing2D)</pre>	(None, 23, 23, 32)	0
conv2d_186 (Conv2D)	(None, 21, 21, 64)	18496
conv2d_187 (Conv2D)	(None, 19, 19, 64)	36928
<pre>max_pooling2d_101 (MaxPool ing2D)</pre>	(None, 9, 9, 64)	0
conv2d_188 (Conv2D)	(None, 7, 7, 128)	73856

```
conv2d_189 (Conv2D)
                                 (None, 5, 5, 128)
                                                         147584
      max_pooling2d_102 (MaxPool (None, 2, 2, 128)
                                                          0
      ing2D)
      flatten_37 (Flatten)
                                 (None, 512)
                                                          0
      dense_132 (Dense)
                                 (None, 128)
                                                          65664
      dense_133 (Dense)
                                 (None, 64)
                                                          8256
      dense_134 (Dense)
                                 (None, 32)
                                                          2080
      dropout_11 (Dropout)
                                 (None, 32)
      dense_135 (Dense)
                                 (None, 7)
                                                          231
     Total params: 363239 (1.39 MB)
     Trainable params: 363239 (1.39 MB)
     Non-trainable params: 0 (0.00 Byte)
      ______
[406]: early_stopping = EarlyStopping(
          monitor='val_loss',
          min_delta=0.0005,
          patience=20,
          verbose=1,
          restore_best_weights=True,
      lr_scheduler = ReduceLROnPlateau(
          monitor='accuracy',
          factor=0.5,
          patience=5,
          min_lr=0.0000001,
          verbose=1,
      )
      callbacks = [
          early_stopping,
          lr_scheduler,
      ]
      history = model.fit(
          trainingData,
```

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epochs=256,
  validation_data=validationData,
  steps_per_epoch= trainingData.n//trainingData.batch_size,
  callbacks=callbacks,
  class_weight=class_weight_dict
model.save('FER1.keras')
Epoch 1/256
0.1543 - val_loss: 1.9593 - val_accuracy: 0.2109 - lr: 0.0100
Epoch 2/256
0.1217 - val_loss: 1.9437 - val_accuracy: 0.1224 - lr: 0.0100
Epoch 3/256
0.1513 - val_loss: 1.9299 - val_accuracy: 0.2177 - lr: 0.0100
Epoch 4/256
0.1691 - val_loss: 1.9538 - val_accuracy: 0.1905 - lr: 0.0100
0.1439 - val_loss: 1.9511 - val_accuracy: 0.0748 - lr: 0.0100
Epoch 6/256
0.2136 - val_loss: 1.9228 - val_accuracy: 0.2109 - lr: 0.0100
Epoch 7/256
0.1899 - val_loss: 1.9251 - val_accuracy: 0.2177 - lr: 0.0100
Epoch 8/256
0.1766 - val_loss: 1.9213 - val_accuracy: 0.2313 - lr: 0.0100
Epoch 9/256
85/85 [============== ] - 1s 6ms/step - loss: 1.9314 - accuracy:
0.1884 - val_loss: 1.9837 - val_accuracy: 0.0544 - lr: 0.0100
Epoch 10/256
0.1736 - val_loss: 1.8747 - val_accuracy: 0.4014 - lr: 0.0100
Epoch 11/256
0.2181 - val_loss: 1.8325 - val_accuracy: 0.4014 - lr: 0.0100
Epoch 12/256
0.2166 - val_loss: 1.8254 - val_accuracy: 0.4150 - lr: 0.0100
Epoch 13/256
85/85 [============== ] - 1s 6ms/step - loss: 1.9028 - accuracy:
0.2418 - val_loss: 1.7592 - val_accuracy: 0.3537 - lr: 0.0100
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Epoch 14/256
0.3205 - val_loss: 1.5843 - val_accuracy: 0.5578 - lr: 0.0100
Epoch 15/256
0.4050 - val_loss: 1.4147 - val_accuracy: 0.4558 - lr: 0.0100
Epoch 16/256
0.4080 - val_loss: 1.2165 - val_accuracy: 0.5374 - lr: 0.0100
Epoch 17/256
0.4614 - val_loss: 1.1388 - val_accuracy: 0.5850 - lr: 0.0100
Epoch 18/256
0.4481 - val_loss: 1.1257 - val_accuracy: 0.5850 - lr: 0.0100
Epoch 19/256
0.5059 - val_loss: 1.1826 - val_accuracy: 0.5714 - lr: 0.0100
Epoch 20/256
0.5193 - val_loss: 1.0302 - val_accuracy: 0.6190 - lr: 0.0100
Epoch 21/256
0.5712 - val_loss: 1.1028 - val_accuracy: 0.5918 - lr: 0.0100
Epoch 22/256
0.5415 - val_loss: 0.9638 - val_accuracy: 0.6054 - lr: 0.0100
Epoch 23/256
0.6206 - val_loss: 0.9548 - val_accuracy: 0.6531 - lr: 0.0100
Epoch 24/256
0.5727 - val_loss: 0.9148 - val_accuracy: 0.6599 - lr: 0.0100
Epoch 25/256
0.6009 - val_loss: 0.9005 - val_accuracy: 0.6939 - lr: 0.0100
Epoch 26/256
0.6320 - val_loss: 1.1208 - val_accuracy: 0.6122 - lr: 0.0100
Epoch 27/256
0.6142 - val_loss: 1.0293 - val_accuracy: 0.6122 - lr: 0.0100
0.6543 - val_loss: 0.8197 - val_accuracy: 0.7211 - lr: 0.0100
Epoch 29/256
0.6691 - val_loss: 0.7415 - val_accuracy: 0.7619 - lr: 0.0100
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Epoch 30/256
0.6662 - val_loss: 0.7877 - val_accuracy: 0.7211 - lr: 0.0100
Epoch 31/256
0.6647 - val_loss: 0.9133 - val_accuracy: 0.6531 - lr: 0.0100
Epoch 32/256
0.7047 - val_loss: 0.7427 - val_accuracy: 0.7687 - lr: 0.0100
Epoch 33/256
0.6914 - val_loss: 1.0835 - val_accuracy: 0.6122 - lr: 0.0100
Epoch 34/256
0.7047 - val_loss: 0.5518 - val_accuracy: 0.8231 - lr: 0.0100
Epoch 35/256
0.7077 - val_loss: 0.7429 - val_accuracy: 0.7415 - lr: 0.0100
Epoch 36/256
0.7240 - val_loss: 0.5543 - val_accuracy: 0.7823 - lr: 0.0100
Epoch 37/256
0.7389 - val_loss: 0.7729 - val_accuracy: 0.6871 - lr: 0.0100
Epoch 38/256
0.7240 - val_loss: 0.5490 - val_accuracy: 0.8095 - lr: 0.0100
Epoch 39/256
0.7448 - val_loss: 0.6767 - val_accuracy: 0.7823 - lr: 0.0100
Epoch 40/256
0.7478 - val_loss: 0.5424 - val_accuracy: 0.8299 - lr: 0.0100
Epoch 41/256
0.7626 - val_loss: 0.5121 - val_accuracy: 0.8571 - lr: 0.0100
Epoch 42/256
0.7507 - val_loss: 0.5448 - val_accuracy: 0.8095 - lr: 0.0100
Epoch 43/256
85/85 [=============== ] - 1s 6ms/step - loss: 0.7201 - accuracy:
0.7685 - val_loss: 0.4164 - val_accuracy: 0.8571 - lr: 0.0100
0.7834 - val_loss: 0.9014 - val_accuracy: 0.6871 - lr: 0.0100
Epoch 45/256
0.7626 - val_loss: 0.4283 - val_accuracy: 0.8503 - lr: 0.0100
```

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Epoch 46/256
0.8012 - val_loss: 0.4199 - val_accuracy: 0.8367 - lr: 0.0100
Epoch 47/256
0.7789 - val_loss: 0.3767 - val_accuracy: 0.8503 - lr: 0.0100
Epoch 48/256
0.8264 - val_loss: 0.4654 - val_accuracy: 0.8503 - lr: 0.0100
Epoch 49/256
0.7878 - val_loss: 0.3278 - val_accuracy: 0.8844 - lr: 0.0100
Epoch 50/256
0.8145 - val_loss: 0.4199 - val_accuracy: 0.8571 - lr: 0.0100
Epoch 51/256
0.8160 - val_loss: 0.4945 - val_accuracy: 0.8367 - lr: 0.0100
Epoch 52/256
0.7849 - val_loss: 0.3030 - val_accuracy: 0.8980 - lr: 0.0100
Epoch 53/256
0.8213
Epoch 53: ReduceLROnPlateau reducing learning rate to 0.004999999888241291.
0.8234 - val_loss: 0.3689 - val_accuracy: 0.8435 - lr: 0.0100
Epoch 54/256
0.8605 - val_loss: 0.3829 - val_accuracy: 0.8435 - lr: 0.0050
Epoch 55/256
0.8605 - val_loss: 0.3869 - val_accuracy: 0.8435 - lr: 0.0050
Epoch 56/256
0.8561 - val_loss: 0.2324 - val_accuracy: 0.9252 - lr: 0.0050
Epoch 57/256
0.8769 - val_loss: 0.2615 - val_accuracy: 0.9116 - lr: 0.0050
Epoch 58/256
0.8635 - val_loss: 0.2479 - val_accuracy: 0.9252 - lr: 0.0050
0.8813 - val_loss: 0.2569 - val_accuracy: 0.9116 - lr: 0.0050
Epoch 60/256
0.9065 - val_loss: 0.2950 - val_accuracy: 0.8980 - lr: 0.0050
```

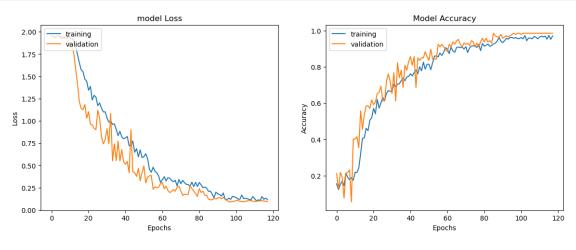
```
Epoch 61/256
0.8991 - val_loss: 0.3079 - val_accuracy: 0.8844 - lr: 0.0050
Epoch 62/256
0.8739 - val_loss: 0.2367 - val_accuracy: 0.9252 - lr: 0.0050
Epoch 63/256
0.9095 - val_loss: 0.2677 - val_accuracy: 0.9116 - lr: 0.0050
Epoch 64/256
85/85 [============== ] - 1s 6ms/step - loss: 0.3612 - accuracy:
0.8887 - val_loss: 0.2189 - val_accuracy: 0.9388 - lr: 0.0050
Epoch 65/256
0.8813 - val_loss: 0.1954 - val_accuracy: 0.9252 - lr: 0.0050
Epoch 66/256
0.9080 - val_loss: 0.2074 - val_accuracy: 0.9456 - lr: 0.0050
Epoch 67/256
0.9110 - val_loss: 0.2301 - val_accuracy: 0.9524 - lr: 0.0050
Epoch 68/256
0.9065 - val_loss: 0.2108 - val_accuracy: 0.9252 - lr: 0.0050
Epoch 69/256
0.9110 - val_loss: 0.2559 - val_accuracy: 0.9116 - lr: 0.0050
Epoch 70/256
0.8991 - val_loss: 0.2651 - val_accuracy: 0.9320 - lr: 0.0050
Epoch 71/256
0.9125 - val_loss: 0.2142 - val_accuracy: 0.9252 - lr: 0.0050
Epoch 72/256
0.8798 - val_loss: 0.1626 - val_accuracy: 0.9320 - lr: 0.0050
Epoch 73/256
0.9050 - val_loss: 0.1776 - val_accuracy: 0.9184 - lr: 0.0050
Epoch 74/256
0.9154 - val_loss: 0.1732 - val_accuracy: 0.9456 - lr: 0.0050
0.9169 - val_loss: 0.1757 - val_accuracy: 0.9388 - lr: 0.0050
Epoch 76/256
0.9154 - val_loss: 0.2740 - val_accuracy: 0.9116 - lr: 0.0050
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Epoch 77/256
0.9080 - val_loss: 0.2393 - val_accuracy: 0.9320 - lr: 0.0050
Epoch 78/256
0.9243 - val_loss: 0.2141 - val_accuracy: 0.9116 - lr: 0.0050
Epoch 79/256
0.8902 - val_loss: 0.1818 - val_accuracy: 0.9388 - lr: 0.0050
Epoch 80/256
0.9303 - val_loss: 0.1523 - val_accuracy: 0.9592 - lr: 0.0050
Epoch 81/256
0.9154 - val_loss: 0.2389 - val_accuracy: 0.9388 - lr: 0.0050
Epoch 82/256
0.9199 - val_loss: 0.1957 - val_accuracy: 0.9592 - lr: 0.0050
Epoch 83/256
0.9273 - val_loss: 0.2101 - val_accuracy: 0.9388 - lr: 0.0050
Epoch 84/256
0.9139 - val_loss: 0.1642 - val_accuracy: 0.9456 - lr: 0.0050
Epoch 85/256
0.9195
Epoch 85: ReduceLROnPlateau reducing learning rate to 0.0024999999441206455.
0.9184 - val_loss: 0.1638 - val_accuracy: 0.9320 - lr: 0.0050
Epoch 86/256
0.9273 - val_loss: 0.1216 - val_accuracy: 0.9864 - lr: 0.0025
Epoch 87/256
0.9318 - val_loss: 0.1153 - val_accuracy: 0.9728 - lr: 0.0025
Epoch 88/256
0.9436 - val_loss: 0.1134 - val_accuracy: 0.9660 - lr: 0.0025
Epoch 89/256
85/85 [=============== ] - 1s 6ms/step - loss: 0.1378 - accuracy:
0.9629 - val_loss: 0.1294 - val_accuracy: 0.9660 - lr: 0.0025
0.9421 - val_loss: 0.1243 - val_accuracy: 0.9796 - lr: 0.0025
Epoch 91/256
0.9347 - val_loss: 0.1331 - val_accuracy: 0.9592 - lr: 0.0025
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Epoch 92/256
0.9451 - val_loss: 0.1410 - val_accuracy: 0.9660 - lr: 0.0025
0.9585 - val_loss: 0.1264 - val_accuracy: 0.9728 - lr: 0.0025
Epoch 94/256
0.9508
Epoch 94: ReduceLROnPlateau reducing learning rate to 0.0012499999720603228.
85/85 [============== ] - 1s 6ms/step - loss: 0.1910 - accuracy:
0.9540 - val_loss: 0.1414 - val_accuracy: 0.9660 - lr: 0.0025
Epoch 95/256
0.9629 - val_loss: 0.1192 - val_accuracy: 0.9728 - lr: 0.0012
Epoch 96/256
0.9629 - val_loss: 0.1057 - val_accuracy: 0.9796 - lr: 0.0012
Epoch 97/256
0.9585 - val_loss: 0.0922 - val_accuracy: 0.9864 - lr: 0.0012
Epoch 98/256
85/85 [============== ] - 1s 6ms/step - loss: 0.1186 - accuracy:
0.9629 - val_loss: 0.0908 - val_accuracy: 0.9796 - lr: 0.0012
Epoch 99/256
85/85 [============= ] - ETA: Os - loss: 0.1525 - accuracy:
0.9570
Epoch 99: ReduceLROnPlateau reducing learning rate to 0.0006249999860301614.
0.9570 - val_loss: 0.0938 - val_accuracy: 0.9864 - lr: 0.0012
Epoch 100/256
0.9570 - val_loss: 0.0990 - val_accuracy: 0.9864 - lr: 6.2500e-04
Epoch 101/256
0.9629 - val_loss: 0.1035 - val_accuracy: 0.9796 - lr: 6.2500e-04
Epoch 102/256
0.9555 - val_loss: 0.1074 - val_accuracy: 0.9864 - lr: 6.2500e-04
Epoch 103/256
0.9733 - val_loss: 0.0947 - val_accuracy: 0.9864 - lr: 6.2500e-04
0.9451 - val_loss: 0.0976 - val_accuracy: 0.9864 - lr: 6.2500e-04
Epoch 105/256
0.9599 - val_loss: 0.0904 - val_accuracy: 0.9864 - lr: 6.2500e-04
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Epoch 106/256
0.9599 - val_loss: 0.0974 - val_accuracy: 0.9864 - lr: 6.2500e-04
Epoch 107/256
0.9555 - val_loss: 0.1010 - val_accuracy: 0.9864 - lr: 6.2500e-04
Epoch 108/256
0.9677
Epoch 108: ReduceLROnPlateau reducing learning rate to 0.0003124999930150807.
85/85 [============== ] - 1s 6ms/step - loss: 0.1195 - accuracy:
0.9688 - val_loss: 0.1065 - val_accuracy: 0.9864 - lr: 6.2500e-04
Epoch 109/256
0.9644 - val_loss: 0.1025 - val_accuracy: 0.9864 - lr: 3.1250e-04
Epoch 110/256
0.9555 - val_loss: 0.1001 - val_accuracy: 0.9864 - lr: 3.1250e-04
Epoch 111/256
0.9659 - val_loss: 0.0931 - val_accuracy: 0.9864 - lr: 3.1250e-04
Epoch 112/256
0.9703 - val_loss: 0.0968 - val_accuracy: 0.9864 - lr: 3.1250e-04
Epoch 113/256
0.9649
Epoch 113: ReduceLROnPlateau reducing learning rate to 0.00015624999650754035.
0.9662 - val_loss: 0.1021 - val_accuracy: 0.9864 - lr: 3.1250e-04
Epoch 114/256
0.9703 - val_loss: 0.1015 - val_accuracy: 0.9864 - lr: 1.5625e-04
Epoch 115/256
0.9540 - val_loss: 0.1036 - val_accuracy: 0.9864 - lr: 1.5625e-04
Epoch 116/256
0.9748 - val_loss: 0.1013 - val_accuracy: 0.9864 - lr: 1.5625e-04
Epoch 117/256
0.9525 - val_loss: 0.0959 - val_accuracy: 0.9864 - lr: 1.5625e-04
Epoch 118/256
0.9708Restoring model weights from the end of the best epoch: 98.
0.9718 - val_loss: 0.0975 - val_accuracy: 0.9864 - lr: 1.5625e-04
Epoch 118: early stopping
```

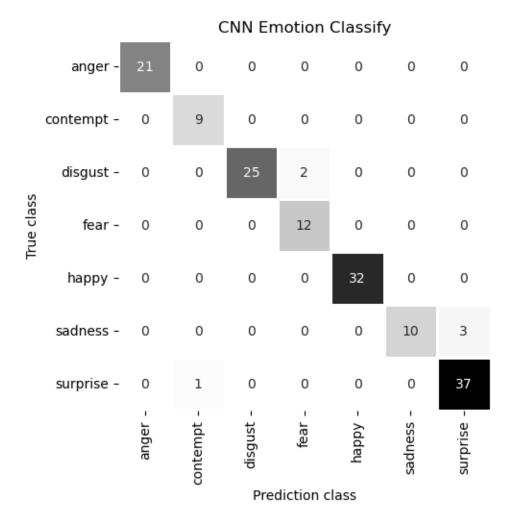
```
[407]: plt.figure(figsize=(14,5))
       plt.subplot(1,2,2)
       plt.plot(history.history['accuracy'])
       plt.plot(history.history['val_accuracy'])
       plt.title('Model Accuracy')
       plt.xlabel('Epochs')
       plt.ylabel('Accuracy')
       plt.legend(['training', 'validation'], loc='upper left')
       plt.subplot(1,2,1)
       plt.plot(history.history['loss'])
       plt.plot(history.history['val_loss'])
       plt.title('model Loss')
       plt.xlabel('Epochs')
       plt.ylabel('Loss')
       plt.legend(['training', 'validation'], loc='upper left')
       plt.show()
```



```
Y_pred = model.predict(testingData)
y_pred = np.argmax(Y_pred, axis=1)
label = ['anger','contempt','disgust','fear','happy','sadness','surprise']
labels = \{0 : 'anger', 1 : 'contempt', 2 : 'disgust', 3 : 'fear', 4 : 'happy', 5_{\sqcup}

    :'sadness',6 :'surprise'}

#Transform to df for easier plotting
cm = confusion_matrix(testingData.classes, y_pred)
cm_df = pd.DataFrame(cm, index = label,
                columns = label
               )
import seaborn as sns
plt.figure(figsize = (5,5))
sns.heatmap(cm_df, annot = True,cmap='Greys',cbar=False,linewidth=2,fmt='d')
plt.title('CNN Emotion Classify')
plt.ylabel('True class')
plt.xlabel('Prediction class')
plt.show()
0.9707
0.9605
final train accuracy = 97.07, validation accuracy = 97.96
19/19 [======= ] - Os 2ms/step
```



```
from keras.utils import load_img, img_to_array
from keras import models
model2 = models.load_model('FER1.keras')

def choose_image_and_predict(image):
    img = cv2.imread(image, cv2.IMREAD_GRAYSCALE)
    img = cv2.resize(img, (48, 48))
    img = img/255
    img = np.expand_dims(img, axis=0)
    img = np.stack([img] * 3, axis=-1)
    pred = model.predict(img)
    label=np.argmax(pred,axis=1)[0]
    return labels[label]

fig = plt.figure(figsize=(10, 7))
```

```
rows = 2
columns = 4
fig.add_subplot(rows, columns, 1)
plt.imshow(load_img("happy.jpg"))
plt.axis('off')
plt.title(choose_image_and_predict("happy.jpg"))
fig.add_subplot(rows, columns, 2)
plt.imshow(load img("sad.png"))
plt.axis('off')
plt.title(choose_image_and_predict("sad.png"))
fig.add_subplot(rows, columns, 3)
plt.imshow(load_img("fear2.png"))
plt.axis('off')
plt.title(choose_image_and_predict("fear2.png"))
fig.add_subplot(rows, columns, 4)
plt.imshow(load_img("surprise.png"))
plt.axis('off')
plt.title(choose image and predict("surprise.png"))
fig.add_subplot(rows, columns, 5)
plt.imshow(load_img("contempt.png"))
plt.axis('off')
plt.title(choose_image_and_predict("contempt.png"))
fig.add_subplot(rows, columns, 6)
plt.imshow(load_img("disgust.png"))
plt.axis('off')
plt.title(choose_image_and_predict("disgust.png"))
fig.add_subplot(rows, columns, 7)
plt.imshow(load_img("anger.png"))
plt.axis('off')
plt.title(choose_image_and_predict("anger.png"))
1/1 [======] - Os 15ms/step
1/1 [======] - Os 14ms/step
1/1 [======] - Os 14ms/step
1/1 [====== ] - Os 13ms/step
1/1 [======] - Os 15ms/step
1/1 [======= ] - Os 14ms/step
```

1/1 [======] - Os 14ms/step

[422]: Text(0.5, 1.0, 'anger')

